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Wake-up with no pain: The Impact of Different Wake-up Ringtones on Awakening Status

Jingzhe Li[1*], Yujia Zhang[2], Jingtian Wamg[3], Hanting Gao[4], Jiawen Liu[5]

[1]Intelligent Sensing Engineering, Shanghai Jiaotong University, Shanghai, Chian, lijingzhe-arctic@sjtu.edu.cn
[2]Biology Science, Zhejiang Chinese Medical University, Hangzhou, China, zYuri815@163.com
[3]Electrical Engineering, Jilin University, Changchun, China, wangjtedward@outlook.com
[4]Merchiston International School, Shenzhen, China, hanting.gao@merchiston.cn
[5]Qingdao academic, Qingdao, China, strict369@gmail.com

Abstract:

The awakening process sets the tone for daily performance. Traditional alarm sounds like radar or sirens, are often abrupt and startling, which can trigger stress response and emotional problems. Existing research that focuses on human physiological indicators during arousal has not reached the impact of wake-up alarms. This study aims to apply photoplethysmographic (PPG) and electrodermal activity (EDA) sensors to meticulously assess the physical and emotional impact triggered by different alarm tones during wake-up process. Those includes human stress responses such as heart rate, EDA, and emotional state. We selected four type of alarm clock sounds, bird singing, ocean sound, radar sound and old telephone. Participants in this study will first put on EDA and PPG sensors before they take a quick sleep. Then, they will be awakened by either natural or harsh wake-up alarms without knowing it in advance. During the experiment, EDA and PPG sensors were used to monitor their physiological states and the data will be analyzed to identify stress patterns and trends. We specially focus on the sudden change when the alarm goes off and the recovery process followed by. The results indicate that participants awaken to harsh alarms had a more intense change in heart rate and emotional stress, while the signal in group of natural sounds was smoother. Our findings provide empirical evidence on the relationship between wake-up alarm sounds and stress responses. There is strong evidence(p-value<0.025) that arousal with more natural sounds causes less heart rate and emotional changes.

Keywords: alarm clock, sleep, wake-up process, stress, PPG.

1. Introduction

An essay published by Frédric Dutheil suggests that sleeping influences one's cognitive performance [1]. Many researchers underscore the effect of sleep on one's mental and physical status, particularly during the period when we first wake up [2]. The awakening process critically sets the tone for later performance [3]. In addition, sound is a significant indicator that influences the physiological state of the human body to varying degrees [4]. Surveys show that 70.15% of people wake up by using an alarm clock [5]. Traditional alarm sounds like radar or sirens, often abrupt and startling, can elicit stress response [6]. Waking up by a sudden alarm can cause dizziness and potentially leading to cardiovascular and psychiatric problems in the long run [7]. The negative effects of being awaken by an alarm clock is proved by Crabb and Peter B that alarm clock use had larger negative correlations with self-regulation ability [8]. Seung-Il and Tsuchiya discussed the association between the phase of a 90-minute periodic signal and the subjective quality of sleeping. This wake-up support system proved that high frequency outside sound can seriously damage our sleep quality [9]. Researchers have thought of many ways to solve this problem. Kumar and Dhiraj designed a smart alarm clock to help the user to wake up gently by increasing brightness and playing the user's favorite music [10]. Landry and Isbell also designed a new generation clock that automatically modify our routines by deciding on an alarm time to improve our sleep quality from alarm clock side [11]. However, those researches overlooked the physiological effects of wake-up alarms. In recent medical studies, mobile health devices have become increasingly popular because of its real-time monitoring ability and wide availability. Those real-time collected data can reflect participants' psychological states and stress level. After processing the raw data with machine learning algorithm, it can tell participants' emotion and its accuracy has reached a high level for electrodermal activity (EDA) and photoplethysmogram (PPG) [12-15]. They are solid evidence that those mobile health devices can detect our data and accurately reflect our health condition. In addition, another study researched the natural and harsh alarm sound features and proved their behavioural impact, which sets a solid base for our study [15, 16]. Our hypothesis is that a sudden change will occur in our EDA and PPG data when the alarm goes off and high-pitched alarm clock leads to a more significant change than natural alarm clock sounds. Besides, harsh alarm clock may increase one's stress level to a extend much higher than the gentle alarm clock.

2. Methodology

2.1 Participants

The study recruited a total of 30 participants aged between 18 and 24 years old (average age was 20.13±1.81), consisting of 17 males and 13 females. Participants must have no history of cardiovascular disease and hearing impairment. Participants were randomly divided into two groups, each with 15 people. Both groups were asked to take a 30-minute nap, with one group being awakened by a harsh alarm clock sound and the other group by a natural alarm clock sound. Participants were informed that they would be awakened with as scheduled alarm clock, but the specific type of sound was not be disclosed. Each participant was required to conduct the experiment alone in a different soundproof room to prevent interference from other sounds. After waking up, they were asked to fill an emotion questionnaire to record the feeling of waking up. The questionnaire example is showed in Table 1.

Table 1. Emotional questionnaire.

Emotion	1 - slightly	2 - a little	3 - moderately	4 - quite a bit	5 - extremely
interested	✓				
excited		✓			
upset			✓		
hostile		✓			
enthusiastic	✓				
irritable				✓	
alert					✓
nervous		✓		✓	
attentive		✓			
active	✓				

2.2 Data collection

Firstly, 30 seconds of excerpts of each ringtone were recorded by auditory recorder in iPhone for frequency domain analysis. A wearable physiological monitoring device was developed based on the Seeed Studio XIAO nRF52840 (Sense) and Expansion Board Base for XIAO. The expansion board was equipped with a battery charging module, an OLED display and a SD card slot. The board featured breakout interfaces for analog signals and serial communication through the Grove connectors. A PulseSensor PPG fingertip sensor Rev1 and an EDA analog sensor based on the Grove interface were connected to the development board via the expansion board. A lithium-ion battery was attached for mobile measurements. The components of the wearable device are showed in Figure 1.

The PPG sensor was affixed to the subject's middle finger tip with adhesive Velcro straps. The EDA sensor was attached using a finger-cot to make sure the electrodes were well contacted with the proximal interphalangeal joints of the index and ring fingers. The schematic diagram of the wearable is depicted in Figure 2. The device was programmed with the Arduino framework. It would start recording the analog data from sensors 3 minutes before the alarm clock setting off and keep recording for another 2 minutes and save data to an SD card.

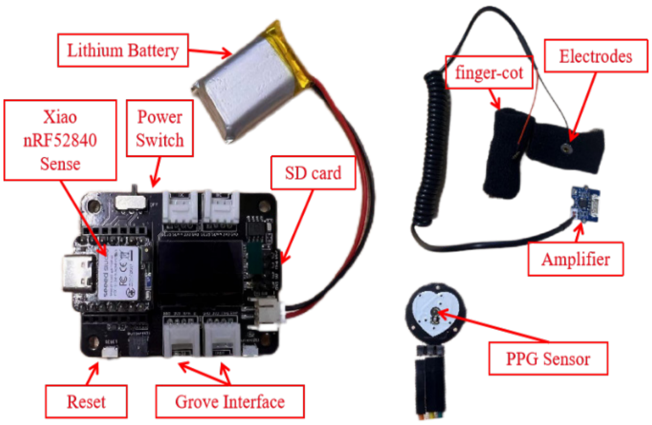

Fig 1. Components of wearable device.

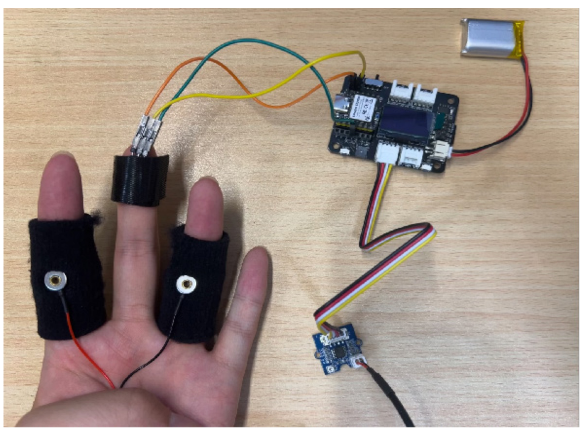

Fig 2. Wearing the device.

2.3 Data analysis

The platform of data analysis was Python. Scipy, numpy, pandas and matplotlib libraires were used to process and visualize data. Firstly, a Fast Fourier Transform (FFT) was applied to the recorded ringtones to conduct a spectral analysis. The ringtones were categorized into harsh and natural groups through the overall energy distribution in the frequency domain [17]. In the process of heart rate signal data processing, the raw PPG signal was initially pass through a low-pass filter with a cutoff frequency of 2.5 Hz to eliminate extraneous noise. Subsequently, the data was segmented by 60-second windows, with each window advancing by one second. Within each window, the peaks were identified and the number of peaks was counted. Then the counts were divided by 60 to determine the heart rate. A continuous record of heart rate variation over a 5-minute period is obtained after the window sliding through the signal. The average heart rate during the first 3 minutes sleeping ($\bar{H}_{sleep}$ in formula (1)) and the maximum heart rate during the awakening process in 2 minutes (H_{max} in formula (1)) were used to define the range of heart rate ($Range$ in formula (1)), as the formula (1) shows. The range serves as a criterion for assessing the magnitude of heart rate fluctuations.

$$Range = H_{max} - \overline{H_{sleep}} \tag{1}$$

The EDA analog signal is processed through a Savitzky-Golay filter to eliminate outliers during measurement [18]. The extent of EDA data variation is assessed by comparing it against a range determined by the average EDA value during sleep and the minimum EDA value upon awakening. The scores from the emotional questionnaire were tallied and the magnitude of the absolute score was used to assess the intensity of emotional fluctuation. Finally, a t-test was conducted to assess the discriminative ability of HRV and EDA ranges under different ringtones, while the Spearman correlation coefficient was employed to determine the correlation between emotional changes and the ranges of HRV and EDA.

3. Results

A total of 30 participants were included in the experiment, consisting of 17 males and 13 females. The harsh ringtone group included 15 participants with average age of 19.58(±1.19), and the natural ringtone group also included 15 participants with average age of 20.67(±2.13). After excluding invalid data caused by poor sensor contact or participants waking up prior to alarm clock—identified by PPG or EDA analog values approaching zero during any periods—there were 24 valid PPG and EDA analog data samples were obtained, with 12 samples from each group.

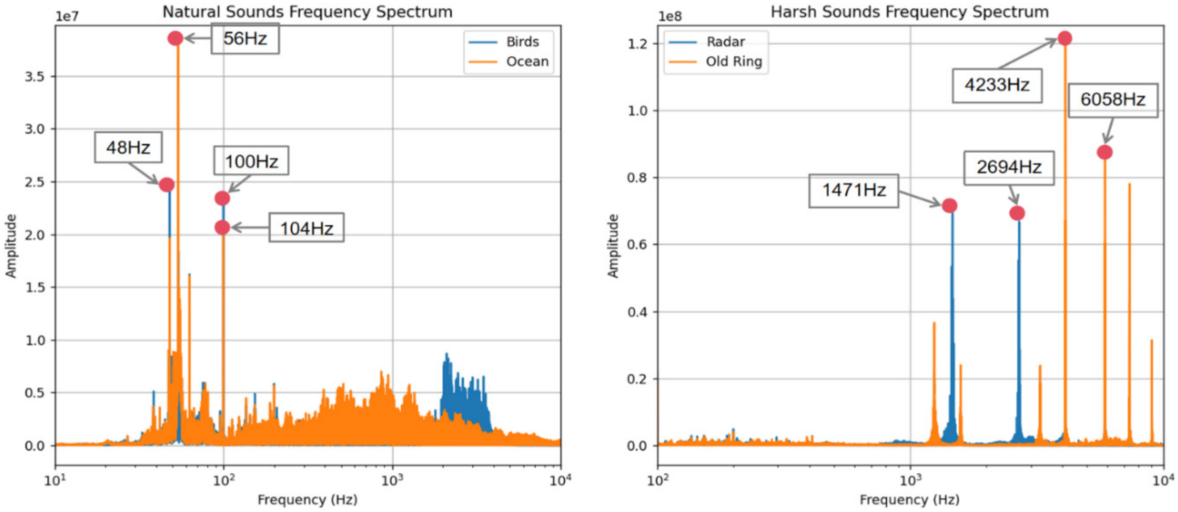

Fig 3. Frequency spectrum of four different kinds of ringtone.

After performing FFT on the four ringtones used in the experiment, the resulting spectrograms are shown in Fig 3. The Birds ringtone (primary frequencies: 48 Hz, 100 Hz) and Ocean ringtone (primary frequencies: 56 Hz, 104 Hz) displayed a smooth distribution of energy across different frequencies. In contrast, the Radar ringtone (primary frequencies: 1471 Hz, 2694 Hz) and Old Ring ringtone (primary frequencies: 4233 Hz, 6058 Hz) had energy concentrated at several specific high frequencies, indicating a comb-like distribution pattern. Thus, Birds and Ocean sounds were categorized as natural ringtone, and Radar and Old Ring were harsh ringtone. Fig 4 shows 6 samples of typical heart rate signal converting from PPG analog signals after applying the filter. The sleep heart rate, maximum heart rate during awakening, and the resulting heart rate range for both groups of participants were obtained. Fig 5 indicates the distribution of the range of heart rate.

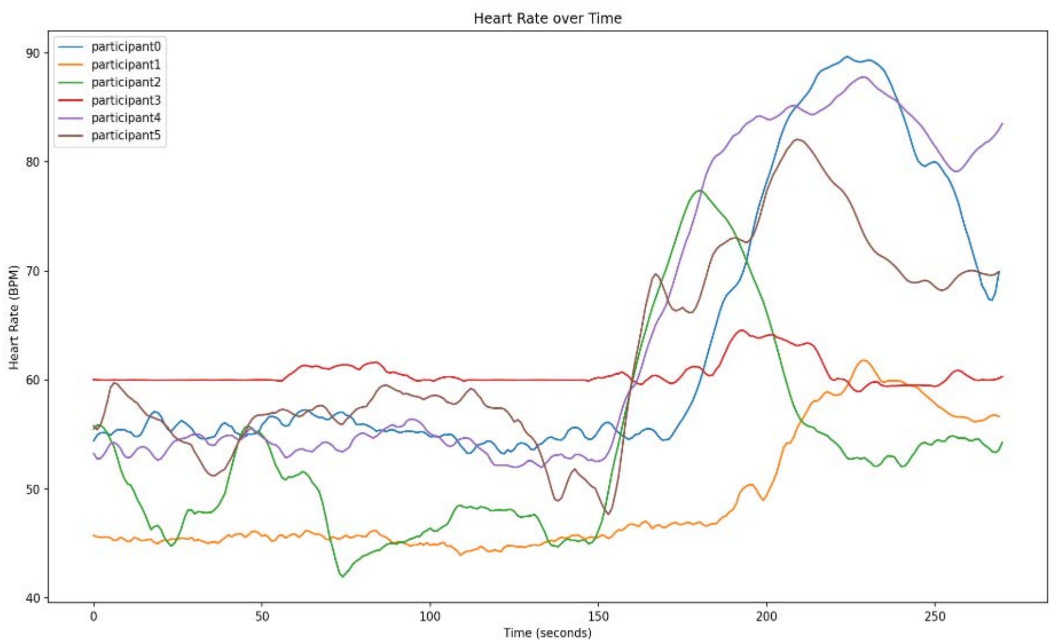

Fig 4. Smoothed Heart Rate Plot.

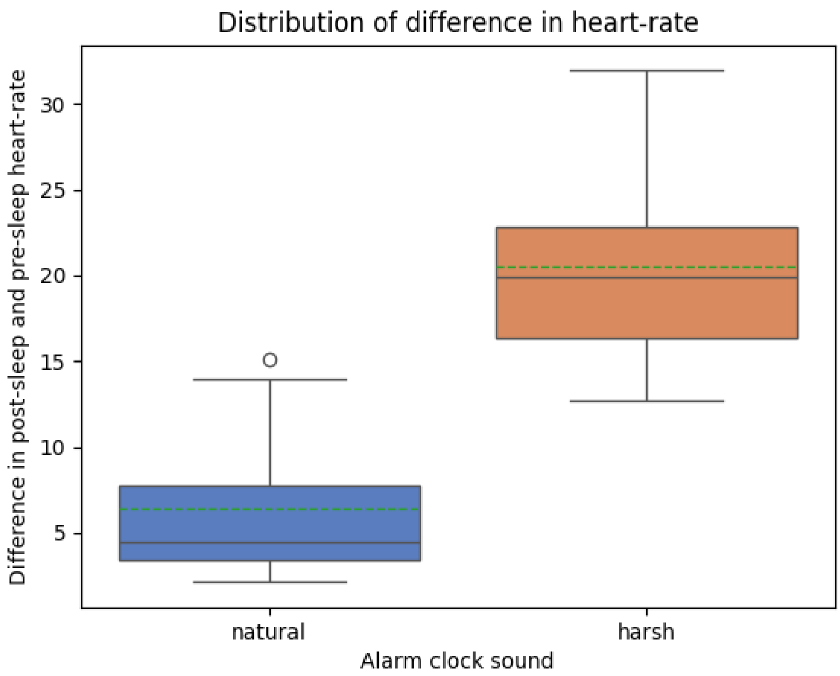

Fig 5. Heart Rate distribution of two groups.

Table 2. Heart Rate Features under Harsh and Natural groups.

ringtone group	heart rate during sleep (BPM)	max heart rate during awakening (BPM)	range of heart rate change (BPM)
harsh	53.29±5.30	73.82±7.96	20.52±5.81
natural	61.07±8.42	67.48±7.56	6.41±4.26

Table 3. EDA Value Features under Harsh and Natural groups

ringtone group	EDA value during sleep	min EDA value during awakening	range of EDA value change
harsh	543.40±44.77	366.88±147.22	176.52±164.51
natural	425.65±186.77	371.21±190.07	54.44±81.46

The relevant statistics (mean and standard deviation) are recorded in Table 2. Fig 6 presents the graphical representation of the EDA analog values for 6 samples after smoothing treatment. Fig 7 illustrates the distribution of EDA analog values under the conditions of “harsh” and “natural” alarm groups. Table 3 lists the average EDA values during sleep and the minimum EDA values upon awakening for both groups, along with the range by these two values, and provides the relevant statistical measures.

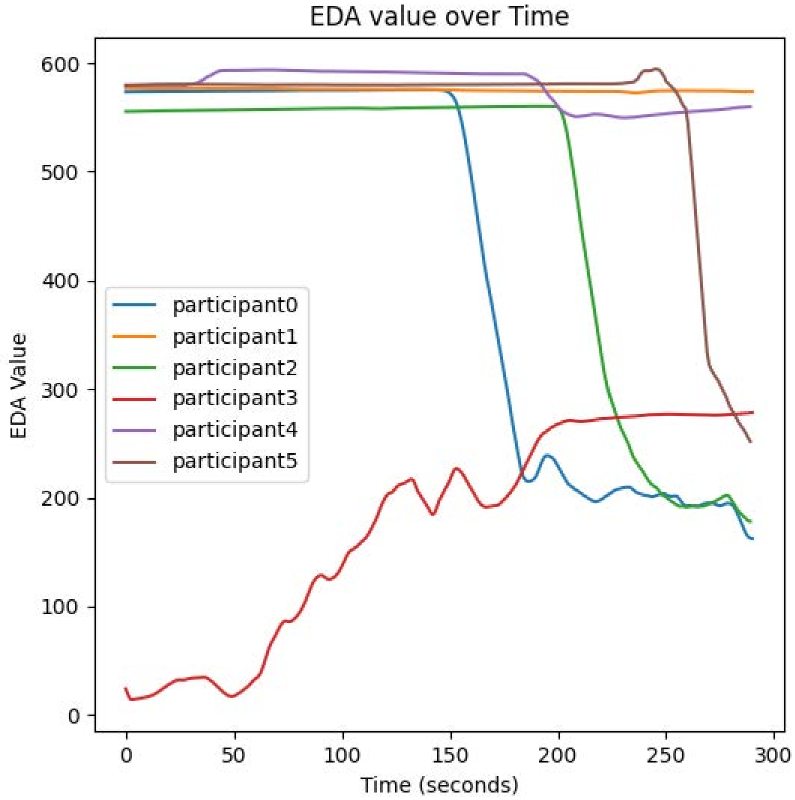

Fig 6. Smoothed EDA value plot.

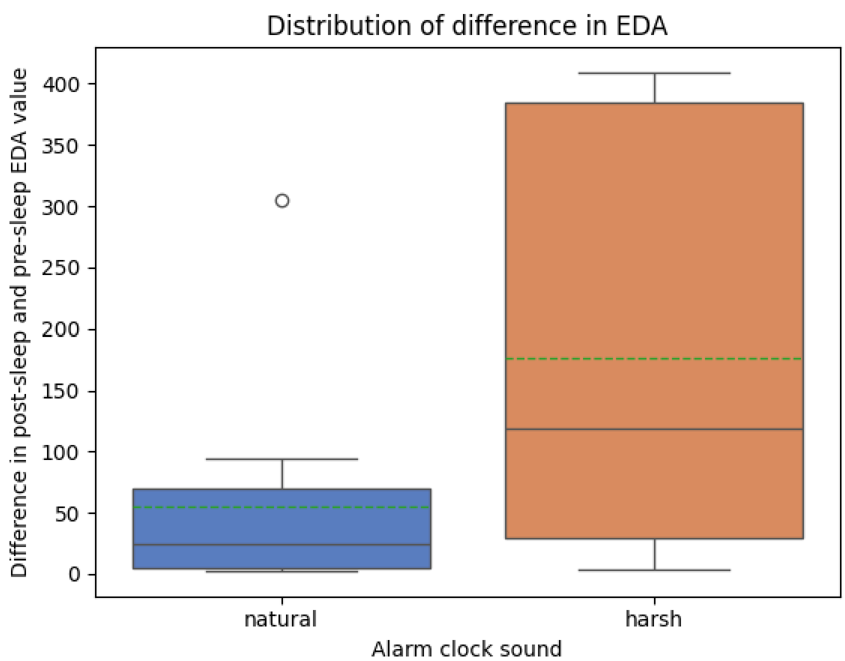

Fig 7. EDA value distribution of two groups.

The scores calculated from the emotional questionnaire from the two groups and relevant statistics are showed in Table 4. Fig 8 shows the distribution of the emotional ratings.

Table 4. Emotion Acores under Harsh and Natural groups.

ringtone group	absolute scores of emotional ratings
harsh	25.33±4.80
natural	17.08±2.43

Table 5. T-test Result and Correlation Coefficient of Heart Rate Range, EDA Range and Emotion.

Statistic variable	value
p-value (heart rate range)	<0.000
p-value (EDA value range)	0.031
ρ (heart rate range – emotion)	0.601
ρ (EDA value range – emotion)	0.325

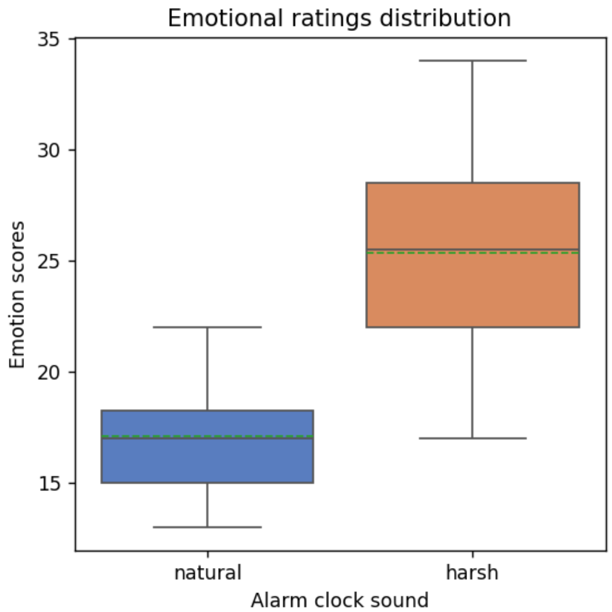

Fig 8. Emotion score distribution of two groups.

Finally, the t-test was conducted to evaluate the discriminative ability of range of heart rate and range of EDA between the two groups. The p-value of t-test and the Spearman correlation coefficients were calculated and are presented in Table 5.

4. Conclusion

This study investigated the impact of various alarm tones on heart rate and EDA during the awakening process. The results demonstrated that harsh alarm tones caused a more pronounced increase in heart rate compared to natural tones. Specifically, the heart rates increased from a baseline of 40-60 bpm to a peak of 80-90 bpm or higher with harsh alarm tones, whereas natural tones resulted in a peak heart rate increase to approximately 70-80 bpm. This difference in heart rate range between harsh and natural alarms was statistically significant ($p < 0.0025$), indicating a gentler waking process with natural sounds. The correlation between heart rate range and emotion ($\rho = 0.601$) suggests a moderate positive relationship, indicating that greater fluctuations in heart rate are associated with stronger emotional responses. In terms of EDA, responses varied widely among participants, with some showing minimal changes and others showing substantial fluctuations in skin conductance. While both EDA and heart rate range showed some discriminative ability, the correlation between EDA and emotional states was weak ($\rho = 0.325$). In contrast, PPG showed a stronger correlation with emotional states, making it a more reliable indicator in this context. The variability in EDA could be attributed to individual differences and external factors such as pre-sleep activities and ambient temperature, which can affect skin conductance reading [20, 21].

Therefore, PPG proved to be more reliable than EDA in reflecting mood changes. The sensitivity of EDA is compromised by environmental factors and physiological noise, which reduces its accuracy in detecting subtle emotional shifts [22]. In contrast, the PPG signal is more stable, thus providing a more precise indicator of autonomic nervous system activity and its relationship to emotional states [23]. The ability of heart rate range to capture physiological responses, especially during arousal, enhances effectiveness the PPG in assessing the impact of alarm tones on mood [24]. By using PPG signal, the accuracy of emotional evaluation gets enhanced and it introduces a new biomarker for optimizing sleep quality monitoring and management algorithms. Consequently, it advanced the understanding and management of how sleep affects mood, thereby improving the performance and reliability of related technologies in practical applications. Additionally, the application of PPG signals facilitates further development of mood detection technology and provides a solid empirical foundation for future research in sleep and mood management. Nevertheless, the study's scope is limited by its narrow demographic sample and age range, which may restrict the generalizability of the findings. To address this limitation, future research should involve a more diverse and expansive participant base to enhance the applicability of these results. Furthermore, incorporating additional physiological and psychological variables, such as hormonal fluctuations and their impact on emotional responses, would offer a more comprehensive perspective on the effects of wake-up stimuli on overall well-being [19]. In summary, this study presents application of PPG to quantify and predict an individual's emotional state upon waking. By comparing range of heart rate and EDA value to the emotional changes, PPG signal serves as a more robust physiological index closely linked to emotion regulation, enabling precise prediction of emotional states during morning awakening.

5. Appendix

All the codes and data are uploaded on Github, link: https://github.com/arctic-aurora123/Wake-up-with-no-pain

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